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# ARTIFICIAL INTELLIGENCE IN LEADERSHIP DISCOURSE (S&P 500 COMPANIES)

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**Abstract:**
This study explores how artificial intelligence (AI) is framed in executive discourse related to leadership and decision-making. The empirical dataset includes 423 interviews with executives from companies listed in the S&P 500, totaling 3,779,645 words. The textual material was collected from the ProQuest database and analyzed using corpus-based lexical analysis with IRaMuTeQ software, which employs automated clustering and semantic classification on large textual datasets. The findings identify three main thematic clusters in executive discussions about AI: education, people, and market dynamics, which together make up 98.29% of the analyzed corpus. Instead of pinpointing causal factors for AI adoption, the results emphasize the predominant discursive frames leaders use when publicly discussing AI-driven organizational change. This study adds to research on AI-enabled leadership by providing extensive empirical evidence of how artificial intelligence is portrayed in executive communication and how these narratives shape leadership discourse on technological innovation.

**Keywords:**
artificial intelligence; leadership; decision-making process; S&P 500 companies.

**JEL Classification:**
M12, 033

## INTRODUCTION

The integration of artificial intelligence (AI) into business operations signifies a notable transformation, surpassing mere technical innovation that fundamentally modifies application domains and theoretical frameworks of leadership theories. AI-driven applications and tools facilitate personalized, diversified, and data-informed interactions between leaders and employees, thereby overcoming the constraints associated with conventional communication methods. This transformation necessitates a comprehensive re-evaluation of the traditional theoretical foundations of leadership. In today's business environment, traditional leadership styles and models face a substantial crisis due to the rise of the most advanced technology. Current practices require predictive analytics, personalization, chatbots, and fast creative ideas.

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In this context, leaders and top executives across various industries have considered modernizing their approach by intensively utilizing AI to augment their decision-making capabilities and attain enhanced efficiency, strategic insight, and accuracy. This tectonic change has generated substantial academic interest, focusing on the key themes associated with leadership and management practices (Haenlein & Kaplan, 2019).

Authors Brynjolfsson and McAfee (2017) stated that utilization of AI-driven decision-making tools provides numerous benefits and advantages for organizations, including the ability to rapidly process vast volumes of data, generate predictive insights, and detect complex patterns. By ultimately enhancing organizational performance, these capabilities empower leaders to make higher-quality, more informed, and timely decisions.

At the same time, integration of AI within any business operation, including leadership, poses specific challenges and risks. These challenges are linked to the biases in AI algorithms, ethical considerations, and leaders' need to cultivate new skills and competencies to leverage these technologies effectively (Duan *et al.*, 2019).

Raisch & Krakowski (2020) stated that there are several reasons that are paramount for understanding the executive discourse of AI-driven decision-making:

- The first reason is that it offers insights into how leaders discuss challenges and advantages associated with AI, which can guide the development of training programs and support systems.
- The second reason is that it illuminates the themes that are semantically associated with the successful implementation of AI within leadership contexts and the acceptance of the most advanced technology.

The disparity between the theoretical benefits of artificial intelligence and the practical managerial experience associated with it presents a noteworthy subject for future scholarly inquiry and useful application. This investigation examines the dominant thematic patterns in leadership discourse related to AI-driven decision-making. By focusing on the perspectives and experiences of leaders, this study aims to elucidate the complex ways in which AI technology can be integrated into strategic leadership practices and decision-making processes.

Despite the increasing body of literature on artificial intelligence in management and leadership, most empirical studies depend on surveys, experiments, or case studies that examine managerial attitudes toward AI technologies. Comparatively, little research has explored how artificial intelligence is framed in executive communication. Public interviews with corporate leaders serve as a key discursive space where organizations express technological strategies, showcase innovation capabilities, and justify technological changes to stakeholders. However, large-scale corpus-based analyses of such leadership discourse remain limited.

To fill this gap, this study analyzes a large corpus of executive interviews to identify the main semantic structures in leadership narratives about artificial intelligence. Instead of focusing on internal executive discourse, the research examines how AI is presented in executive communication.

The study is guided by the following research questions.

**RQ1**: What main thematic structures characterize executive discourse on artificial intelligence in leadership communication?

**RQ2**: How are these themes organized semantically within large-scale textual corpora of executive interviews?

**RQ3**: What discursive frames shape leadership narratives about AI adoption and organizational change?

The findings offer new insights into how artificial intelligence is communicated and understood in executive leadership discourse. The rest of the paper is organized as follows: Section 2 reviews relevant literature, Section 3 describes the research methodology, Section 4 presents the empirical findings, and Section 5 discusses the results and concludes the study.

## LITERATURE REVIEW

### Artificial Intelligence in Decision-Making: Advantages vs. Challenges

The integration of artificial intelligence (AI) into leadership roles and decision-making processes has become notably evident in recent years. Technologies such as data analytics, machine learning, and natural language processing have revolutionized organizational approaches to resolving corporate issues, strategic planning, and enhancing operational efficiency. Consequently, AI has assumed a vital role across numerous sectors and industries. The enhancement of effectiveness and efficiency in managerial decision-making is facilitated by the employment of advanced tools and techniques (Makarius *et al*., 2020).

AI technologies have advanced to better support decision-making processes. For example, machine learning algorithms are now capable of analyzing extensive datasets to generate predictive models and recognize patterns. These models assist in evaluating financial risks, forecasting customer behavior, and anticipating market trends. Additionally, natural language processing (NLP) enables the extraction of meaningful information from unstructured data sources, such as social media posts and textual documents, thereby improving decision-making areas such as competitive intelligence and sentiment analysis (Galanis *et al.*, 2021). Machine learning, also known as reinforcement learning, has become another highly utilized AI technology. It has demonstrated significant potential in decision-making applications. This methodology proves itself beneficial, especially in dynamic environments such as stock trading and supply chain management. It also enables systems to acquire optimal corporate strategies through iterative experimentation. Recent progress in AI explainability has facilitated greater comprehension and trust of AI-generated recommendations among leaders (Gunning & Aha, 2019).

AI has been applied across various sectors to enhance decision-making processes. In the financial sector, AI models are now utilized for fraud detection, credit scoring, and investment strategies, significantly reducing human error and increasing efficiency (Chowdhury, Dey, *et al.*, 2023). In healthcare, AI-driven tools assist clinicians by providing timely and precise diagnoses, leading to improved patient outcomes (Esteva *et al.,* 2019). For example, in manufacturing, AI-powered predictive maintenance facilitates the forecasting of equipment failures, thereby minimizing downtime and operational costs (Wang *et al.,* 2018). The significance of AI in marketing is even more pronounced; AI is redefining marketing strategies through targeted advertising and personalized recommendations, thereby enhancing customer

engagement and conversion rates (Davenport *et al.*, 2020). According to Gama & Magistretti (2023), one of AI's most vital potentials lies in its ability to provide unprecedented capabilities for predictive analytics and real-time insights, especially in strategic decision-making.

Despite numerous benefits, several challenges arise in the adoption of AI for decision-making. The availability and quality of data remain substantial obstacles. AI systems require large volumes of high-quality data to operate effectively; however, acquiring such datasets is often challenging due to privacy concerns and data silos (Kleinberg *et al.*, 2017). Leaders must ensure that employees are aware of relevant regulations protecting sensitive information (Shin & Park, 2019). Furthermore, integrating AI into existing systems and workflows can be complex and resource-intensive, frequently necessitating significant process modifications and organizational restructuring (Brynjolfsson & McAfee, 2017).

Another critical issue pertains to the ethical implications of AI. AI algorithms may perpetuate existing biases present in the training data, resulting in discriminatory outcomes and unfair judgments (Bolukbasi *et al.*, 2016). Addressing this responsibility requires the development of robust governance frameworks and the promotion of diversity within AI development teams (Bolukbasi *et al.*, 2016) to sustain trust in AI-driven decision-making processes (Floridi *et al.*, 2018). Moral leadership in the age of AI demands a commitment to transparency, accountability, and prioritization of societal well-being over short-term gains (Schwartz *et al.*, 2019).

## The Evolving Role of Leadership in the Age of AI

Artificial Intelligence (AI) is fundamentally transforming various facets of management and business practices, including leadership. Over the past decade, the role of leaders has undergone significant evolution. Numerous new challenges and opportunities have arisen within the current dynamic global environment. As AI technologies become integrated across diverse organizational processes, the fundamental role of leadership remains consistent. Leaders are now required to possess traditional management skills alongside a comprehensive understanding of the implications of AI. Consequently, leadership must prioritize modernization and the adoption of AI within its strategic frameworks (Dahlke & Ebersberger, 2023).

In the emerging AI epoch, conventional leadership competencies are no longer sufficient to ensure competitiveness. New skills and attributes now augment these traditional attributes. Leaders must develop a deeper understanding of AI technologies and their potential impacts on organizational performance (Wilson & Daugherty, 2018). Such technological proficiency enables leaders to make better-informed decisions regarding the adoption and implementation of AI. Additionally, cultivating data literacy is imperative for leaders to interpret AI-generated insights accurately and leverage them effectively (Ransbotham *et al.*, 2017). The central question arises: how can leaders maintain human-centric approaches amidst the rapid adoption of AI technology (Chowdhury *et al.*, 2022)? The answer resides in continuous learning and adaptation, enabling organizations to harness AI for strategic advantages (Jain *et al.*, 2023).

Leaders must also develop strategic thinking as a vital competency to envisage and strategize for the long-term implications of AI. The deployment of AI influences organizational strategy and operations (Westerman *et al.*, 2014). This involves anticipating shifts within the dynamic global landscape and identifying innovative opportunities. Alongside strategic thinking, emotional intelligence remains essential, as leaders must preserve a humanistic approach toward their personnel. Managing the human aspects of AI integration involves fostering a culture of continuous learning and addressing employee

concerns (Huang & Rust, 2018). Transparent communication constitutes a fundamental leadership skill. Leaders are tasked with articulating strategic messages concerning AI to all stakeholders, ensuring employees understand how AI will impact their roles and the overall work environment (Kolbjørnsrud *et al.*, 2017). Such transparency fosters trust and mitigates resistance to change (Floridi *et al.*, 2018).

Organizational culture is significantly influenced by AI integration within the workplace. Leaders play a crucial role in shaping organizational culture to facilitate successful AI adoption. Cultivating a culture that values agility, innovation, and change is vital for effectively leveraging AI (Bughin *et al.*, 2017). Leaders should foster an organizational atmosphere in which experimentation is encouraged, and failures are regarded as opportunities for learning.

## Qualitative Studies of AI in Decision-Making

As previously discussed, Artificial Intelligence (AI) is revolutionizing decision-making processes within organizations. Understanding how leaders frame and interact with these new technologies is crucial for further practical implementation and utilization. Top managers often discuss AI as both an opportunity and a challenge, balancing the benefits of improved decision-making capabilities with concerns related to operational and ethical implications (Chowdhury, Joel-Edgar, *et al.*, 2023). While previous qualitative research has explored comparable dynamics, it reveals a wide spectrum of attitudes – ranging from skepticism to enthusiasm – largely driven by individual familiarity with AI and the surrounding organizational culture (Keding & Meissner, 2021). These discourses will shape further integration and adoption of AI in managerial practices, depending on tailored training and support (Chalmers *et al.*, 2021).

In the study published by Jarrahi (2018), top managers discuss several benefits of integrating AI. Processing vast amounts of data and identifying patterns that may not be evident to humans. This data-driven approach leads to more effective and informed final decisions. Davenport (2018) posited that AI enhances efficiency by automating routine tasks, thereby allowing leaders to dedicate more time to strategic thinking. In the same study, Davenport also highlighted that managers appreciate AI's ability to forecast outcomes and trends, aiding in proactive decision-making and strategic planning. Authors Brock & Von Wangenheim (2019) proved that AI technology tools can improve customer insights, allowing personalized marketing and better customer relationship management. In their study, Ransbotham *et al.* (2017) talked about the complexity of AI systems and the need for continuous learning to keep up with technological advancements. Technological advancements may introduce potential biases in AI algorithms that must be understood for the purposes of accountability and fairness (Danks & London, 2017). At the same time, Glikson & Woolley (2020) raised the point about trust in verified AI-generated recommendations. Shrestha *et al.* (2019) proved that AI adoption targets both organizational structure and culture significantly. Managers must recognize this shift to a more data- and technology-driven culture, where decisions are based on empirical evidence rather than professional intuition.

The following authors examined the change in leadership styles. Effective leaders are those individuals who can fill the gap between new technological requirements and human insights, fostering human collaboration between employees and AI systems (Khan *et al.*, 2024; Wilson & Daugherty, 2018). On the other hand, ethical leadership is crucial in managing the complexities of AI deployment in alignment with organizational values and societal norms (Floridi *et al.*, 2018).

Besides technological and organizational perspectives, leadership communication serves as a significant analytical lens for comprehending how artificial intelligence is contextualized within managerial discourse. Executive communication often fulfills a symbolic and legitimizing role, shaping executive discourse of technological transformation and organizational strategy. Leaders frequently craft narratives that highlight innovation, capability development, and strategic adaptation to legitimize technological investments and signal competitiveness (Fairhurst, 2007). From this vantage point, public interviews with executives can be viewed not merely as sources of information but also as discursive artifacts that mirror how organizations communicate technological change.

## RESEARCH METHODOLOGY

The research paper employs a top-down approach that incorporates selected keywords to construct specific sub-clusters from the primary text corpus. These sub-clusters pertain to the subject of intangible assets.

### Use of Iramuteq Software in Management Sciences Research

The application of Iramuteq software in qualitative research constitutes a significant methodological decision within the realm of management sciences, especially for investigations into complex phenomena such as AI-driven decision-making in leadership. Iramuteq, an open-source analytic tool, is crafted for textual data examination and provides comprehensive methods for content analysis, including word frequency analysis, cluster analysis, and co-occurrence analysis, which are vital for thoroughly exploring qualitative data (Camargo & Justo, 2013). The principal developer of this software is Pierre Ratinaud of the Laboratory LERASS at the University of Toulouse, France, who initiated its development in 2008. The software integrates the 'Bibliometrix package' from R software, representing the text corpus, and was developed in Python to facilitate complex textual analysis. Another significant benefit of using Iramuteq in management research is its transparency and replicability. The software's open-source nature ensures that the analysis process is transparent and can be replicated by other researchers, thus contributing to the robustness of the study. This is particularly important in the field of management sciences, where the complexity of human behavior and organizational dynamics necessitates rigorous and reproducible research methodologies (Albertini *et al.*, 2021; Bardin, 2011).

The use of Iramuteq software in the qualitative analysis of executive discourse of AI-driven decision-making offers substantial methodological benefits. Its capabilities in handling large volumes of text, performing sophisticated analyses, and providing clear visualizations make it an invaluable tool for researchers in the management sciences. By leveraging these strengths, researchers can gain deeper insights into the complexities of leadership and decision-making in the context of artificial intelligence.

### Research Material and Research Sample

The corpus for this study was sourced from the ProQuest textual database provided by Clarivate. It comprises 423 in-depth interviews conducted with leaders and top executives of companies listed on the S&P 500 index. The data collection period covered January 1, 2025, to January 1, 2026. The final dataset consisted of 1.549 pages. Qualitative analysis was employed on the selected corpus. The IRaMuTeQ software, which includes its own English business dictionary, facilitated a more comprehensive understanding of the textual content. This analysis reveals word frequencies, groupings, and the strength of relationships between clusters.

This study analyzes publicly available interviews with corporate executives, emphasizing discursive patterns in leadership communication rather than internal managerial cognition or decision-making processes. Since executive interviews are influenced by corporate communication strategies and impression management, the findings should be viewed as reflecting the prevailing discursive frameworks leaders use when publicly discussing artificial intelligence and organizational change.

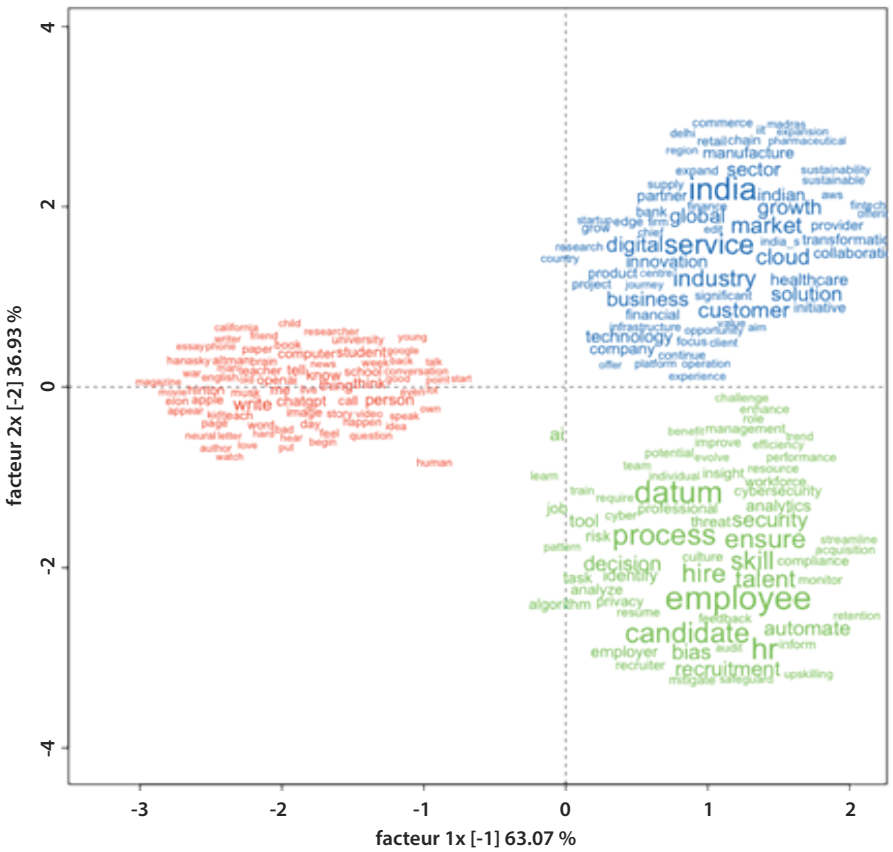
## FINDINGS AND DISCUSSION

The research study had two phases. We implemented a step-by-step procedure that was executed according to the following criteria.

### First phase: analyzing the entire textual corpus in order to reveal the main categories of the interviews in the examined companies

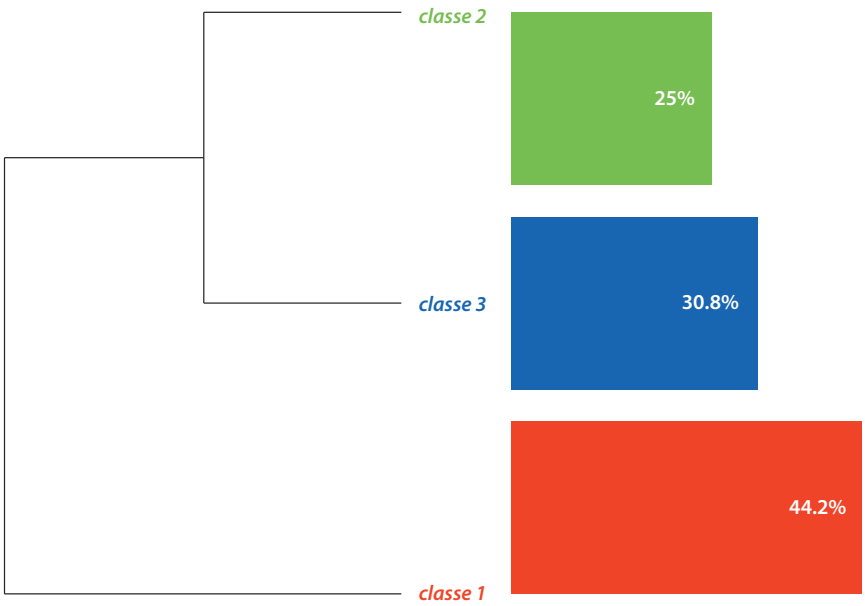
This phase included 423 interview articles (texts), 3,779,645 words, 16,867 text segments, and 23,348 forms. What is significant is that the analysis covered 98.29% of the corpus, which means that the three clusters covered almost the whole corpus text. More precisely, this percentage has 17,716 lemmas, 16,801 active forms, and 6,322 hapaxes (words that are only included in the three main clusters). The paper identified three main categories or clusters (Figure 1).

**Figure 1.** Semantic clouds of 3 categories of leadership interviews




*Source: Authors' calculation*

**Figure 2.** Dendrogram of 3 main clusters of the corpus




*Source: Authors' calculation*

**Table 1.** Categories revealed in the research study phase 1

| Category | Color code | Name | % of forms analyzed |
|---|---|---|---|
| Category 1 | Red | Education | 44.2% |
| Category 2 | Green | People | 25% |
| Category 3 | Blue | Market | 30.8% |

*Source: Authors' calculation*

All three categories are related to the topic of AI. Category 1 – Education is the first and most visible factor (school, computer, teacher, professor, University, learning, book, brain, mind, lesson, knowledge etc.). Category 2 – People discuss human capital (employee, candidate, HR, process, skill, hire, talent, recruitment, job, workplace, professional, workforce, culture, personalize, feedback, potential, human, etc.). Category 3 – Market covers the terminology related to market indicators (demand, supply, price, competition, growth, customer, sector, industry, collaboration, expand, commerce etc.)

By analyzing the results, we may conclude that all three themes are closely related to the primary subject of Artificial Intelligence (AI). In Figure 1, it is observable that the Category is highlighted in red. This category is distinctly separated from the other two categories. Categories 2 and 3 demonstrate a close association. Category 1 accounts for 44.2%, Category 2 for 25%, and Category 3 for 30.8%. In Figure 1, the three principal categories or variables are depicted within the factor plan. A factorial plan generates distances and strength indicators between variables. The X-axis, or abscissa, represents the distance and distribution of variables. Greater proximity between variables represents a stronger positive association within the analyzed corpus. The Y-axis, or ordinate, indicates the strength or tangibility of the relationships between the selected variables. The position of each variable in the factorial plan is particularly significant. Category 1 is situated in the quadrant of negative abscissa and negative ordinate.

Category 2 occupies the region of positive abscissa and negative ordinate. Category 3 is positioned in the quadrant where both the abscissa and the ordinate are positive. From these observations, it can be inferred that all three variables are in close proximity, suggesting a strongly tangible relationship. The extent of influence among them primarily depends on their respective positions within the factorial plan. In Figure 2, the proximity of Categories 2 and 3 to Category 1 in the factorial correspondence analysis suggests a strong semantic association among discussions of workforce capabilities, market dynamics, and educational development in executive discourse on artificial intelligence.

In the subsequent phase, sub-corpora will be created from each cluster to facilitate the generation of more precise indicators. This second-level analysis will enable a more focused examination of the three categories.

## Second phase: creating sub-corpora from the text corpus

The second phase concentrates on generating sub-corpora from the initial corpus to elucidate Categories or Clusters 1, 2, and 3. This clarification aims to enhance the comprehension of the designated category (Figure 3). The second phase comprises three sub-stages:

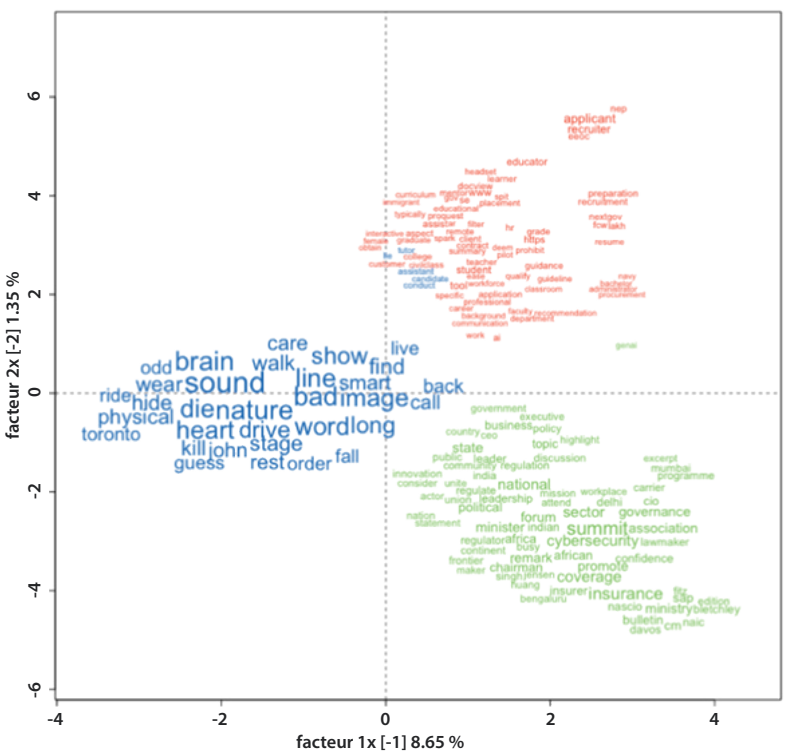
Creation of a sub-corpus from Cluster 1 – Education;

Creation of a sub-corpus from Cluster 2 – People;

Creation of a sub-corpus from Cluster 3 – Market.

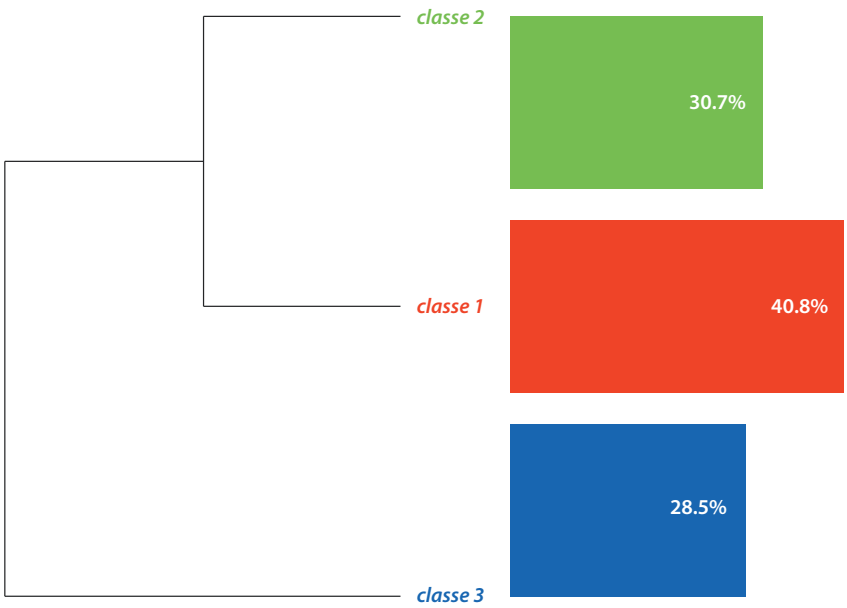
## Creation of a sub-corpus from Cluster or Category 1 – Education

**Figure 3.** Creation of sub-semantic clouds from corpus text (Category 1)




*Source: Authors' calculation*

**Figure 4.** Dendrogram of 3 main clusters of a sub-corpus text (Category 1)




*Source: Authors' calculation*

**Table 2.** Categories revealed in the research study phase 1

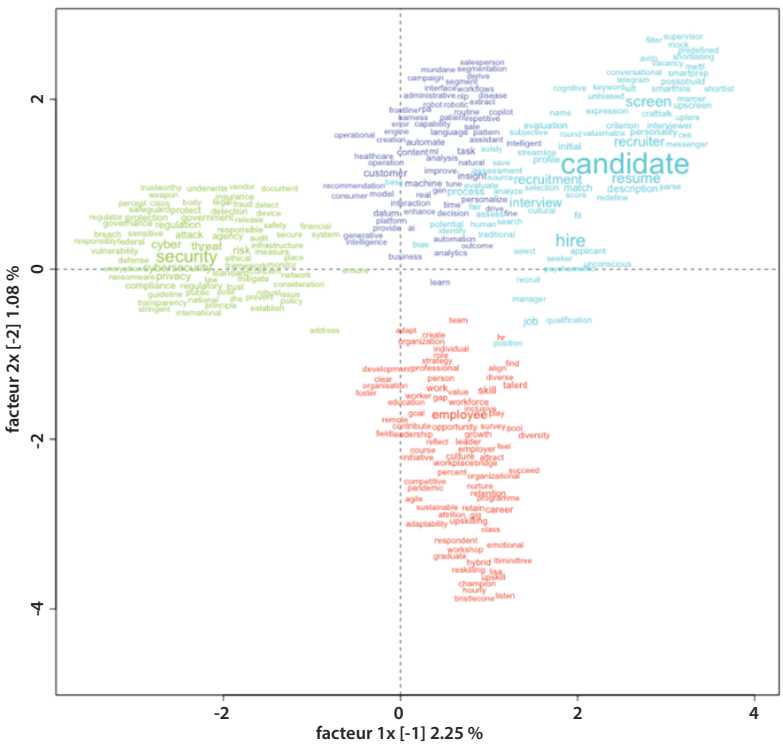
| Category | Color code | Name | % of forms analyzed |
|---|---|---|---|
| Category 1 | Red | Science | 40.8% |
| Category 2 | Green | Governance and national economy | 30.7% |
| Category 3 | Blue | Students | 28.5% |

*Source: Authors' calculation*

In the first sub-corpus, Cluster 1 is represented by 40.8% red, Cluster 2 by 30.7% green, and Cluster 3 by 28.5% blue. Cluster 1 focuses on science, Cluster 2 addresses governance and the national economy, and Cluster 3 pertains to students. Specifically, Cluster 1 encompasses themes related to research, innovations, R&D, and funding. Cluster 2 discusses topics such as state governance, inflation, fiscal policy, monetary policy, interest rates, and public administration. Finally, Cluster 3 covers aspects related to students, including graduates, studies, admissions, college programs, and colleagues.

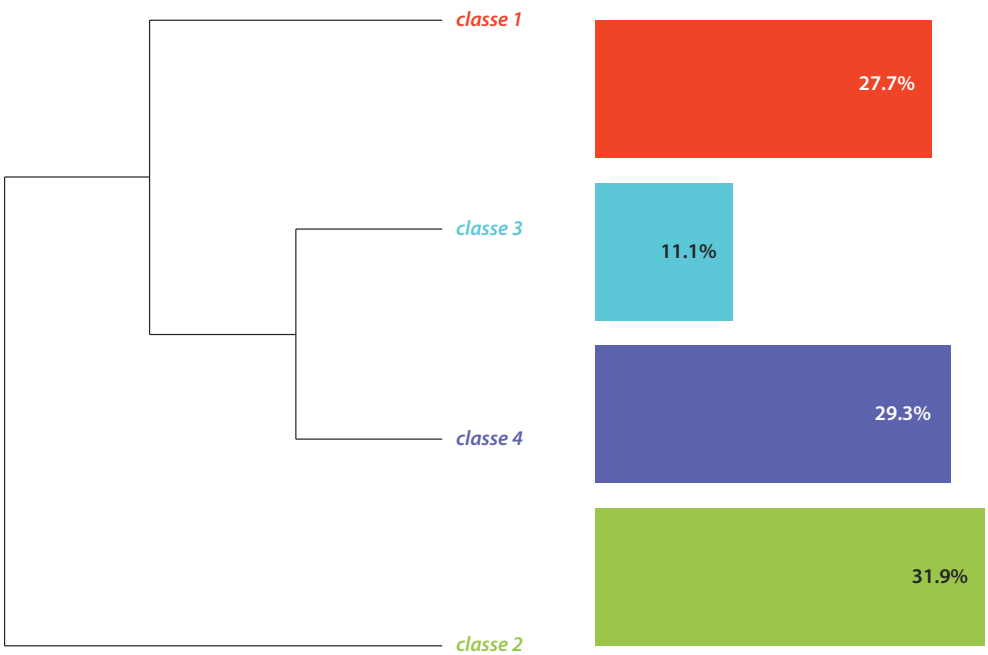
## Creation of a sub-corpus from Cluster or Category 2 – People

**Figure 5.** Creation of sub-semantic clouds from a corpus text (Category 2)




*Source: Authors' calculation*

**Figure 6.** Dendrogram of 3 main clusters of a sub-corpus text (Category 2)




*Source: Authors' calculation*

**Table 3.** Categories revealed in the research study phase 1

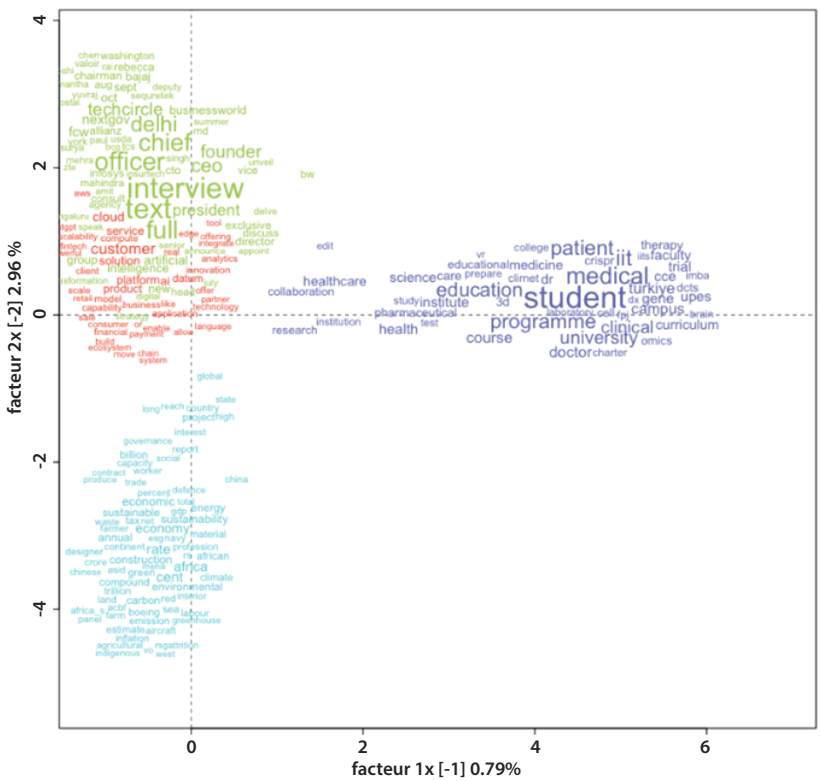
| Category | Color code | Name | % of forms analyzed |
|---|---|---|---|
| Category 1 | Red | Cyber security | 27.7% |
| Category 2 | Green | Recruitment process | 31.9% |
| Category 3 | Blue | Work automation | 11.1% |
| Category 4 | Purple | Skilled employees | 29.3% |

*Source: Authors' calculation*

In the second sub-corpus related to People, Cluster 1 is represented by 27.7% red, Cluster 2 by 31.9% green, Cluster 3 by 11.1% blue, and Cluster 4 by 29.3% purple. Cluster 1 focuses on cybersecurity, Cluster 2 on the recruitment process, Cluster 3 on work automation, and Cluster 4 on skilled employees. Specifically, Cluster 1 encompasses themes such as security, data privacy, data protection, attacks, compliance, threats, the Internet, agencies, and related topics. Cluster 2 addresses the recruitment process, including candidates, matching, interviews, screening, resumes, evaluation, smart hiring, assessments, job fairs, and other related aspects. Cluster 3 covers work automation, discussing automation, machinery, analysis, operations, efficiency, repetitive workflows, generative processes, robots, computers, algorithms, and more. Cluster 4 emphasizes the importance of employees' skills and experience, highlighting talent, upskilling, opportunities, retention, workplace culture, and other relevant topics.

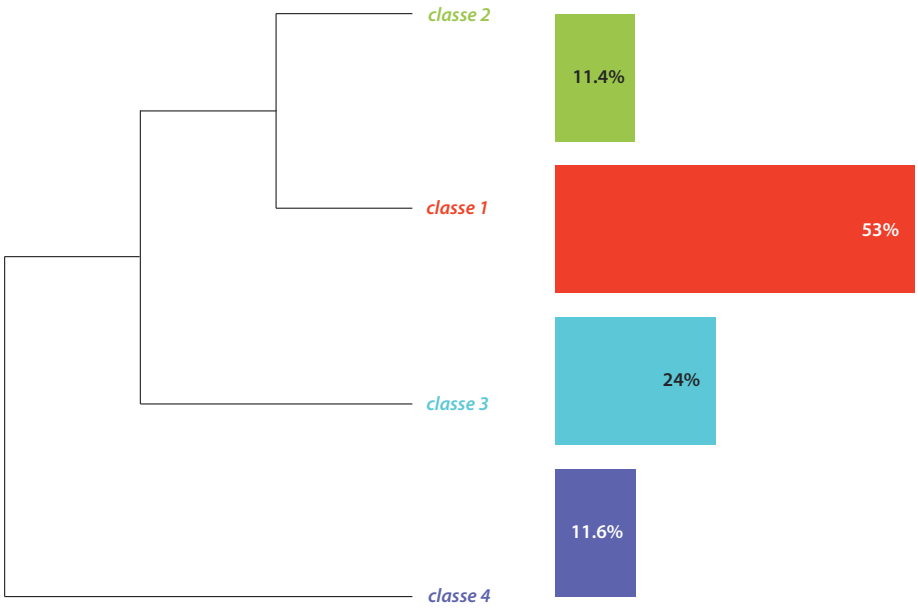
## Creation of a sub-corpus from Cluster or Category 3 – Market

**Figure 7**. Creation of sub-semantic clouds from a corpus text (Category 3)




*Source: Authors' calculation*

**Figure 8**. Dendrogram of 3 main clusters of a sub-corpus text (Category 3)




*Source: Authors' calculation*

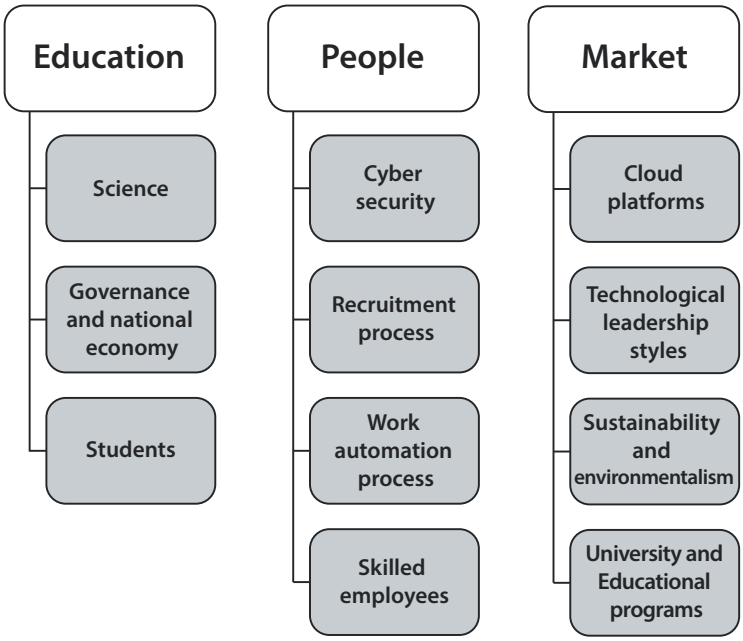
**Table 4.** Categories revealed in the research study phase 1

| Category | Color code | Name | % of forms analyzed |
|---|---|---|---|
| Category 1 | Red | Cloud platforms | 53% |
| Category 2 | Green | Tech leadership styles | 11.4% |
| Category 3 | Blue | Sustainability and environmentalism | 24% |
| Category 4 | Purple | University programs | 11.6% |

*Source: Authors' calculation*

In the third sub-corpus related to the Market, Cluster 1 is represented by 53% red, Cluster 2 by 11.4% green, Cluster 3 by 24% blue, and Cluster 4 by 11.6% purple. Cluster 1 focuses on cloud platforms, Cluster 2 on technology leadership styles, Cluster 3 on sustainability and environmentalism, and Cluster 4 on university programs. Specifically, Cluster 1 encompasses themes such as cloud, platforms, solutions, services, AI, products, customers, models, computing, scalability, technology, and related topics. Cluster 2 addresses leadership in technology, including interviews, officers, CEOs, founders, tech circles, presidents, AI, executives, directors, chairmen, CTOs, digital transformation, and other related aspects. Cluster 3 covers sustainability, discussing energy, the environment, carbon, green initiatives, climate, emissions, heating, pollution, and more. Cluster 4 emphasizes university programs, highlighting students, programs, education, universities, colleges, courses, campuses, institutions, faculty, offerings, curricula, academics, and other relevant topics.

**Figure 9.** Categories and sub-categories




*Source: Authors' calculation*

The results of the lexical clustering analysis show that executive discourse on artificial intelligence centers on several main thematic areas. In contemporary discussions on artificial intelligence (AI) technology, leaders frequently emphasize three pivotal themes: education, the human factor, and market dynamics.

- Firstly, the importance of education is a recurrent topic. Executive discourse frequently emphasizes education as a central theme in discussions of AI utilization. Comprehensive and ongoing educational initiatives are deemed crucial for equipping individuals and organizations with the necessary skills and knowledge to harness AI's potential. Without a robust academic foundation, it is challenging for any organization to fully realize the benefits of AI implementation.
- Secondly, the discourse highlights the indispensable role of people in AI innovations and projects. Leaders consistently underline that human input and expertise are prominently emphasized for the successful development and deployment of AI technologies. The role of people is portrayed as both inevitable and irreplaceable, emphasizing that AI advancements rely heavily on human creativity, decision-making, and ethical considerations.
- Ultimately, market needs and demands are a central focus of the conversation. Narratives indicate the importance of understanding and responding to the constantly evolving market landscape. Executive narratives highlight adaptability as an important element to stay competitive. This adaptability is critical in navigating the dynamic environment of market demands and technological advancements.

The integration of artificial intelligence (AI) in leadership decision-making processes has been extensively examined, with numerous scholarly articles addressing similar themes. Wamba-Taguimdje *et al.* (2020) emphasize how AI enhances business process management through the provision of advanced analytics and decision support systems, thereby leading to improved operational efficiency and decision quality.

Likewise, Kakatkar *et al.* (2020) analyze the paradoxes associated with AI in management, noting both the augmentation of managerial capabilities and the challenges, such as the necessity for new skills and potential resistance from employees. Borges *et al.* (2021) investigate AI's role in decision-making within the context of big data, highlighting benefits such as enhanced data processing and pattern recognition, while also discussing issues related to data quality and ethical considerations. Keding and Meissner (2021) underline the importance of balancing AI's analytical capabilities with human intuition in leadership decisions. The study indicates that major pharmaceutical companies place significant emphasis on their corporate communication narratives in public news dissemination. Mikalef and Gupta (2021) emphasize the importance of dynamic capabilities – namely, adaptive, absorptive, and innovative capacities – for organizations to effectively leverage AI technologies.

Collectively, these studies underscore the transformative potential of AI in leadership decision-making, while also illuminating the complexities and challenges associated with its deployment. The insights derived from these scholarly works suggest that the successful integration of AI into decision-making processes requires not only technological adoption but also a strategic approach to change management and fostering collaboration between human and artificial intelligence agents.

## CONCLUSIONS

This study explored how artificial intelligence is portrayed in executive leadership discussions. By analyzing a substantial collection of interviews with corporate leaders through automated lexical clustering, the research uncovered three main thematic areas – education, people, and market dynamics – that shape leadership narratives on AI. These themes highlight the primary discursive frameworks used by executives to discuss AI's role in organizational change. The dataset included 423 interviews and 3,779,645 words across 1,549 pages of text. Notably, the study encompassed 98.23% of the entire corpus, thereby confirming the dominance of the identified thematic clusters in leadership discourse on AI. The main findings identified three dominant thematic clusters: Education, People, and Market as prominent thematic elements in executive discourse. Greater transparency in corporate communication by top leadership may also help lessen investor scrutiny and provide reassurance during crises.

Several limitations should be acknowledged. First, the study relies solely on publicly available interviews with corporate executives, which may reflect corporate messaging strategies and impression management rather than authentic internal managerial reasoning. Second, the dataset mainly includes large publicly listed companies, potentially limiting the applicability of the results to smaller firms or different organizational contexts. Third, while the lexical clustering method detects semantic patterns in discourse, it does not directly assess managerial attitudes, decision-making behaviors, or organizational outcomes related to AI adoption. Future research could integrate corpus-based approaches with interviews, surveys, or case studies to compare public leadership discourse with internal managerial practices.

Overall, this study provides valuable insights into AI's evolving role in the corporate world. As AI continues to develop, it is vital to adopt a human-centered approach that balances AI's benefits with the protection of human autonomy, expertise, and ethical standards.

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